

Knowledge-Building Support through Social Navigation in Learning Community

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Abstract—In information search on Web as learning activities, by utilizing social bookmarks as a mechanism to classification and organization of the collected information, tags are added when individual learners bookmark a Web page, to be shared. In this paper, we describe the method for building knowledge models by analyzing the structure and the temporal nature of tags to estimate the knowledge structure of learners and learning community. We propose supporting information search on Web based on the knowledge model, and a mutually supportive learning environment to achieve knowledge building in the learning community.

Keywords—Learning Community; Information Search; Social Bookmark; Knowledge Structure; Ant Algorithm.

I. INTRODUCTION

With the development of social web technologies, Internet-based learning activities have become increasingly diverse. In particular, the learning support focused on knowledge sharing in communities formed by Wiki, Blog, Wiki, Blog, and SNS (Social Network Service) have been actively researched. On the other hand, in the technology to support information search on Web, social navigation and social search have been remarkably widespread [1] [2]. Reflecting that, the learning support utilizing social navigation [3] [4] has been attracting attention.

In this research, our purposes are to support information search on Web as a learning activity, and to promote of mutual support for building knowledge in the learning community. We perform our purpose by utilizing the technology of social bookmarking to realize social navigation based on the concept of sharing bookmarks. Also, in this paper, we define the group of learners sharing the common learning objectives taken from the viewpoint of knowledge, skills and applications, problem solving, as "Learning Community".

By utilizing social bookmarks, they consider the classification of a bookmark pre-arranged, they add to the bookmark information (e.g., title, URL, and evaluation) the equivalent of a bookmark metadata called "tag", and they register them on the Web site. Social bookmark is a social web technology to share and manage tags by multiple users. Tags associated with the Web pages based on user's knowledge, represents the user's own expertise [5]. In

addition, differences in the classification system for Web pages by tagging interact in communication between users, and influence the formation of community.

When analyzed in terms of the Bloom's Taxonomy of Learning, learners who use tags show evidence of moving up the hierarchy from the lower "consumption"-based levels of learning (knowledge and comprehension) to higher levels of applied and metacognitive knowledge (application and analysis). Further, reviewing of tags (i.e., comparing tags used by a community of taggers) would potentially facilitate the move to the highest levels of Bloom's Taxonomy of Learning (synthesis and evaluation) [4].

Therefore, in this paper, in inquiry learning including information search process on Web depending interests and purposes of individual learners to achieve the learning objectives, we propose a knowledge-building support by utilizing social bookmarking as a mechanism to classification and organization of the collected information. First, in information search on Web as learning activities, we provide support by the navigation of Web pages based on the knowledge model of learners and learning community. Next, we will provide mutual support for building knowledge in the learning community, by encouraging participation to the community, and by recommending members to the community.

The paper is as follows. In Section 2, we discuss related work, and examine the use of social bookmark to support knowledge-building in the learning community. In Section 3, as our research approach, we explain how to create the knowledge model of learners and learning communities. Then, we propose social navigation based on the knowledge model of the learning community. In Section 4, we describe overviews of our system and the details of important processing module. In Section 5 shows a running example and discuss the preliminary experiment. In Section 6, we describe future plans.

II. RELATED WORK

Social navigation [6] is a technique to support the activities of learners by using information about other learning activities. For example, learning support using bookmarks, links, and annotation [3] in learning activities, has been researched. In this section, we describe related research studies focusing on social bookmarks created by

collaborations in the community. Then, we discuss creating learner's model utilizing social bookmarking, and examine techniques to support knowledge-building.

A. *Social Navigation and Learning Support*

Social navigation is intended to support information search using bookmarks, links, and annotations created by a collaboration of the community [1] [2]. Farzan [3] realized learning support using the AnnotatEd (Annotations for Education) by incorporating the annotation to provide social navigation in e-Learning. In addition, Bateman [4] focused on the potential educational benefits of collaborative tagging proposed by John [5], and developed collaborative learning system OATS (Open Annotation and Tagging System) as an open source tool. Bateman showed the possibility of adaptation of collaborative tagging on e-Learning by analyzing learner's tagging, automatic tagging provided by system, and expert's (instructor) tagging for e-Learning contents, from data obtained by experiments. However, any support is limited in the areas that the learning content domains in e-Learning. For information search on Web, learning support has not been done according to interests and purposes of individual learner. Also, the environment as the interaction between learners is not provided.

In this research, in inquiry learning activities on Web, we provide an environment for social navigation and community as a learning support by utilizing social bookmark applying the capabilities of collaborative tagging and Folksonomy (i.e., classification by people).

B. *Social Bookmark and Learner's Knowledge Model*

John [5] proposed two methods for ranking ExpertRank to quantify the expertise of the user in the context of a specific tag. One is a simple way that is not expected in the relationship between the tags on unstructured tag space, the other is a realistic way that assumes the classed tag space. In the latter method, each cluster of tags can be represented graphically. Nodes represent tags, and edges between nodes represent the strong contextual relationship between tags.

ExpertRank, instead of determining all areas of expertise for a specific user, that is important to find a user who is familiar with a specific area. However, the temporal aspects of the tag have not been considered. So, Michlmayr [7] proposed the Add-A-Tag algorithm for profile construction, which takes account of the structural and temporal nature of tagging data, as a complementary approach to John's proposals. Michlmayr extended the co-occurrence approach [5] with the evaporation technique known from Ant algorithms, in order to consider the time course of the bookmark. However, the relationships between the tags are not the result of a community-driven process, but entirely created by one user instead. Hence, the relationships between the tags might not make sense to anyone except to the user who created them.

In this research, our system accumulates, as learning history, tags granted to a Web page when individual learners bookmark, and semantic tag consisting features of Web pages, rating, registration date. We extract tags that represent concepts from the stored data. By analyzing timing of the

appearance of concept tags and subsequent relationship between concept tags considering the temporal aspects, we estimate the knowledge structure of learners and learning community. Thus, we represent model of their knowledge to the graph.

C. *Social Bookmark and Navigation*

Social bookmark has achieved social navigation by the recommendation of Web pages based on information obtained through the sharing of useful bookmarks. The methods of navigation are classified as recommendation by analyzing the contents bookmarking, recommendation by analyzing the co-occurrence, and recommendation of the graph-based user model by analyzing the structure of tags.

As a graph-based recommendation, Sharma [8] applied the strategy of evaporation of the pheromone of ants to deal with the temporal nature of the tags that Michlmayr [7] proposed. Their method is different from the way to add weight to the edges of Michlmayr. In the proposals of Michlmayr, the evaporation is done at all edges and the weights are added to the specific edge. In the proposals of Sharma, if not already present as nodes in a graph of all the tags associated with a specific user at a specific time, nodes are added with equal weight. Then, evaporation is performed on the existing edges, which consists of tags provided by users than the specific user. Thus, the recommendation considering the temporary user interest has been discussed and that it is beneficial to specific users. However, if a specific user provides tags, we consider evaporation is reasonable to be done on the edges, which consists of tags provided by the specific user.

In this research, we also apply the update strategies of the Ant Algorithm to the time course of the tag. However, our approach is different from related research in terms of the method to update the edge weights and to reflect the recommendations of dynamic interest and purpose in the community using the knowledge structure of the learning community.

D. *Social Bookmark and Community*

The concept of community is the basis for social Web. Lacher [9] discussed that members of the community can facilitate communication because members share perspectives common to observe the real world, and vocabulary, common concepts and common system of concepts are prescribed in terms of this common. Based on this basic concept, Ogure [10] proposed the method for automated information retrieval system utilizing the concept of experts as the community ontology. However, in the method of Ogure, there are problems that the cost of building the community ontology is high, and non-experts have to search for information using unfamiliar ontology of experts. In these problems, Bateman's [4] results of a comparative analysis of tagging by learners and experts showed that to be effective Collaborative tagging. On the other hand, Freyne [2] proposed a method to collect the wisdom of the community by integrating social search and social navigation.

Therefore, our approach is utilizing the knowledge structure of the learning community built by social

bookmarking as community-particular conceptual system, to support the individual learner's information search. In addition, by implementing the search function of learning communities and community members, we provide mutual support for building knowledge in the community.

III. OUR PROPOSED APPROACH

In the learning cycle assumed by our research, first, we describe how to create the knowledge model of learners and learning communities. Then, we propose the method for social navigation based on the knowledge model of the learning community. After, we describe how to encourage participation for mutual support for building knowledge in the learning community.

A. Learning Cycle

In this research, as shown in Figure 1, we assume learning cycle to repeat "Search", "Browse", and "Classification and Organization by Bookmarks" on Web [11].

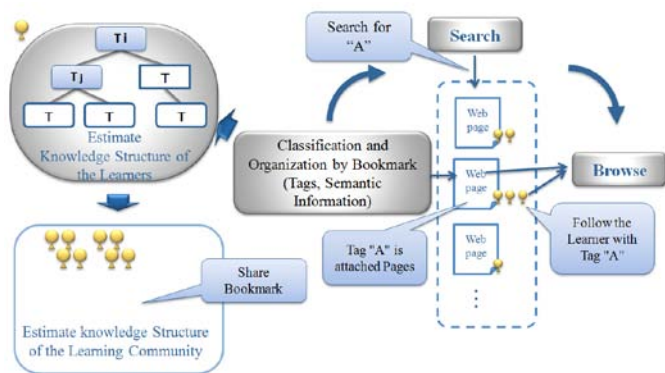


Figure 1. Learning Cycle

First, learners search by keywords or tag cloud (list of tags) for individual interest and purpose. Then, they select a page from the list including the title of Web page, URL, etc. that is presented as a search result to browse for their interests and purposes. When they bookmark the pages they visit, they store tags and semantic information in the system and work together to classification and organization of Web pages.

In this system, log data of tagging behavior in information search on Web (i.e., the title and URL of Web page bookmarked, important keywords), tags and semantic information (purpose of the tag, reading amount, difficulty and importance, usefulness, registration date) is stored in a database as a learning history.

B. Knowledge Model of Learners and Learning Community

In this system, target learner's model of learning support is created based on the accumulated history of individual learning. We determine from semantic information of individual learning history and extract the tags that represent

the concept. Then, we represent learner's knowledge model to the graph containing the concept tags extracted as nodes, and co-occurrence as edges. Moreover, as with the proposal of Sharma, we apply the update strategy of Ant algorithm to the weight of the edge of the graph by considering the passage of time. However, our method is different from the way to add weight to the edges of Sharma. We proposed to make the evaporation on the graph that consists of tags of target learner. Because, if the target learner will make a new tag, target's interest will fade from existing tags. Thus, the graph of other learners is not affected, but the graph of the learning community will be affected.

The graph of a learner $G = (V, E)$ has node set V and edge set E where: $V = \{v_1, v_2, \dots, v_n\}$ is (corresponding to tags t_1, t_2, \dots, t_n) and $E = \{e_1, e_2, \dots, e_n\}$. If tags t_i and t_j appear at the same time, the edge corresponds to tags t_i and t_j , the weight assigned to the edge is represented as w_{ij} . We describe the weight w_{ij} update procedure, as follow: (1) to (3).

- If there is not v_i , all tag t_i will be added to the graph as a vertex v . (1)

- Evaporation is performed using the following formula on the existing edges, which consists of specific learner's tags.

$$w_{ij} = (1-p) * w_{ij} \tag{2}$$

- If there is an edge between vertices v_i and v_j , the weight (w_{ij}) is as follow:

$$w_{ij} = w_{ij} + \beta \tag{3}$$

Here, β is a real constant, $\beta > 0$.

Otherwise, it will be added as a weight $w_{ij} = \alpha$ to the edge between vertices v_i and v_j .

Here, α is a real constant, $\alpha > 0$.

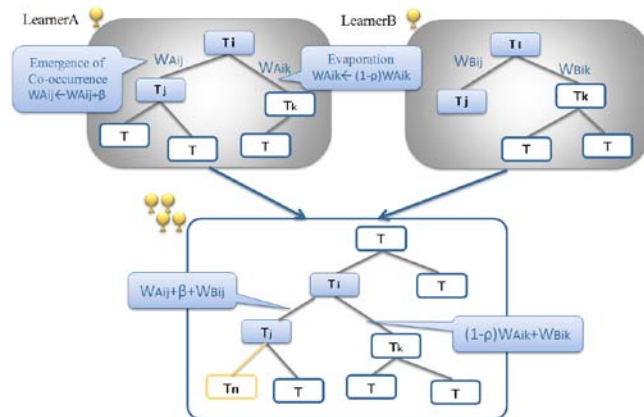


Figure 2. Knowledge Model of Learners and Learning Community

On the other hand, the knowledge model of the learning community is created based on the learning history of learners that participates in the community. Similar to the learner's knowledge model, we represent the knowledge model of the learning community to the graph. Here, the weight w_{ij} of the edge corresponding to the tags t_i and t_j is the sum of edge weights w_{ij} corresponding to the tags t_i and t_j of the individual learner. Once the update is made under the weight of the individual learner, the update will be done in the community. Thus, the dynamic interest and purpose of individual learners will be reflected in the community.

C. Social Navigation using the Knowledge Model of Learning Community

As stated previously, our system will also create the knowledge model of the entire system (i.e., social), while creating the knowledge model of learners and learning community.

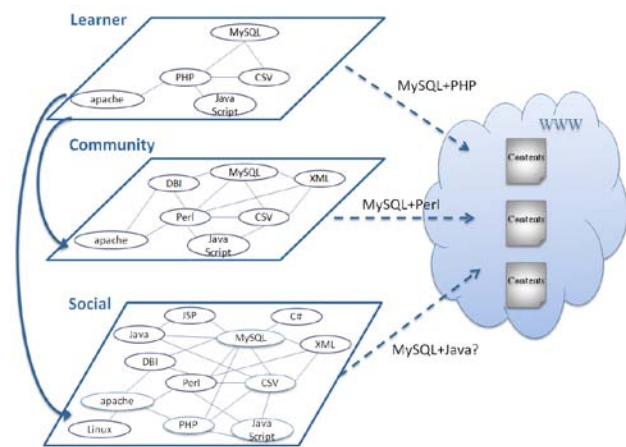


Figure 3. Social Navigation utilizing the Knowledge Model of Learning Community

Therefore, as shown in Figure 3, if a learner will participate in the learning community with a aim, for example, if the learner has learned "PHP" will participate in the learning community has learned "Perl" already with the aim of learning "Perl", to support to explore the appropriate Web pages for search keywords of the learner, based on the knowledge model of the learning community, our system extracts concept tags needed by the target learner, and recommends the Web pages associated highly with those tags. For example, if the learner's search keyword is "MySQL", the traditional social bookmarking sites recommend highly relevant pages with "MySQL". However, they are not always highly relevant pages with "Perl". If the system recommends based on the learner's past history, it recommends highly relevant pages with "PHP". On the other hand, if our system recommends using the dynamic knowledge structure of the learning community, it reliably recommends highly relevant pages with "Perl", which has been formed in the community at that time.

D. Mutual Support for Building Knowledge in Learning Community

In this system, by implementing the search function of the learning community, it would recommend the learning community to adapt for learner's new interest and purpose, based on the knowledge model of learners and the community. In addition, it presents the community recommended in the page of "Learning Community Bookmark".

On the other hand, by implementing the search function of members for additional members of the learning community, it would recommend additional learners needed to achieve the objective of the learning community, based on the knowledge model of learners and learning community seeking additional members. In addition, it presents the member recommended in the page of "Learner's Bookmark". By the recommendation of members and learning communities, it promotes the participation of the community for mutual support for building knowledge in the learning community.

IV. SYSTEM CONFIGURATION

As shown in Figure 4, our system is comprised of "Social Bookmark Database" and the seven processing module. Among them, the following describes the details of important processing module in the learning community; "Community Bookmark Management", "Community Bookmark Recommendation", "Learning Community Recommendation", and "Community Member Recommendation".

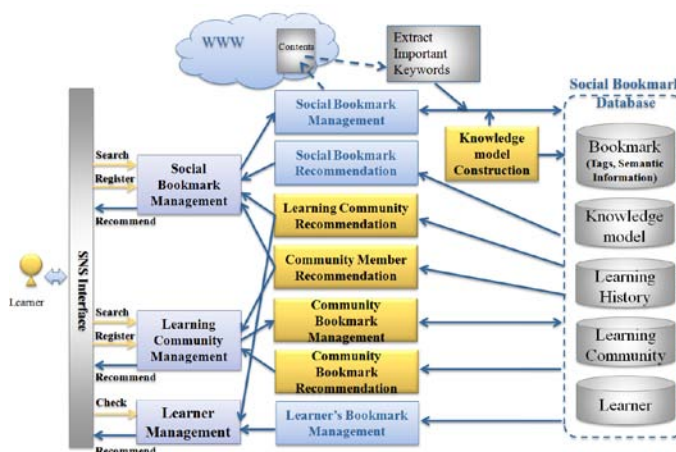


Figure 4. System Configuration

A. Community Bookmark Management Module

In learning communities, this module performs main processing; to search information, to represent search results, and to register tags and semantic information at the time of bookmarking. Learners enter b), d), h), i), and j) of Figure 5 by themselves during the registration. Otherwise, our system automatically extracts, and store in the database. In

addition, it extracts the concept of tags based on "Content Theme", "important keywords in the content" in i), and items without "after" in h). Mainly, Learners search by keywords or tag cloud, and store tags and semantic information in our system when they bookmark the pages they browse. Our system automatically extracts the title of a Web page and keywords at URL that learners entered during registration, and stores them in the database.

a) Tag-ID	b) Tag-Name	c) Category
d) URL	e) important keywords (contained in 4.)	
f) Learner-ID	g) Registration Date	
h) Reading Amount: •all •half •some •diagonally •after		
i) Purpose of the tag		
Objective: •Content Theme		Concept Tags
•Important Keywords in the content		
•Type of the content (news, blogs, and articles)		
•Content Author		
Subjective: •Content Comments		
•The procedure to use the content (preparation, review, and reference)		
•Relevance of their content (own blog, post comments)		
j) Characterized of the content		
Difficulty:	•Difficult •Normal •Easy	
Importance:	•High •Normal •Low	
Usefulness:	•Useful •Normal •Useless	

Figure 5. Tags and Semantic Information

Also, in Community Bookmark Management Module, our system has performed navigation by presenting high ranked pages calculated based on the knowledge model of the learning community from the top of the search results.

B. Community Bookmark Recommendation Module

The consensus among learners in the learning community that are built in the community is done on special Web page classification using particular tags. Also, as shown in Figure 2, the weight of edges in the graph of the knowledge structure of learning communities is the sum of the weight of the corresponding edges of each learner. Thus, dynamic interest and purpose of individual learners will be reflected, and the knowledge structure of the community is continually updated and is codified by evaporation. So, based on the dynamic knowledge structure of the learning community, our system recommends Web pages tagged with particular tags related search keywords in the community. Thus, we navigate common keywords in the community and relevant knowledge has become a subject of interest and purpose.

First, in order to narrow the search results with related tags for search keywords, our system extracts tags to recommend in the learning community. If there is a node in a graph of the knowledge structure of the community, our system extracts the edges with Top-k weights connecting the node to the other nodes, and recommend tags combined of the search keywords and the extracted node tags. Then, by the relevance between Web page and tags to recommend,

we obtained in accordance with the following calculation method to rank the page. Our system presents high ranked pages from the top of search results.

The page's rank is calculated as follow:

Calculate the relevance between the page P and tag T.

$$P = \Sigma W_i \quad (4)$$

(W_i is the important keywords contained in the page P)

Let the relevance between the page P and the tag T be $rel(P, T)$,

$$rel(P, T) = \Sigma rel(W_i, T) \quad (5)$$

Here, $rel(W_i, T)$ and T is the relevance between W_i and T.

Thus, the page rank is calculated as follow:

$$\text{page's rank} = \Sigma rel(P, T_j) = \Sigma \Sigma rel(W_i, T_j) \quad (6)$$

C. Learning Community Management Module

1) Recommendation of the Learning Community:

Our system calculates CommunityRank for search keywords, and presents high CommunityRank communities from the top of search results. In the page of "Learner's Bookmark", the search keywords is the tags in the learner's most recent bookmarks.

CommunityRank is calculated as follow:

The graph of the learner's knowledge structure $G = (V, E)$ has node set V and edge set E where: $V = \{v_1, v_2, \dots, v_n\}$ is (corresponding to tags t_1, t_2, \dots, t_n) and $E = \{e_1, e_2, \dots, e_n\}$. Where a set of keyword search is $K = \{k_1, k_2, \dots, k_m\}$, and k_i is an element of K, $k_i \in V$, if there is $e_{ij} \in E$, e_{ij} is the edges corresponding to a tag $t_i (= k)$ and t_j , and the weight represented as w_{ij} . This time, let a set of t_i and t_j with Top-k (w_{ij}) be V_{Top} . On the other hand, let the graph of the knowledge structure of the learning community be $G_c = (V_c, E_c)$. Where $V_{Top} = \{v_1, v_2, \dots, v_n\}$, an element of V_{Top} is $v_i \in V_c$, if there is $e_c \in E_c$, the weight of the edge e_c represented as w_{cij} .

Thus, CommunityRank is calculated as follow:

$$\text{CommunityRank} = \Sigma w_{cij} \quad (7)$$

2) Recommendation of the Community Member:

Our system calculates MemberRank for search keywords, and presents high MemberRank learners from the top of search results. In the page of "Learning Community Bookmark", the search keywords is the tags in the learner's most recent bookmarks.

MemberRank is calculated as follow:

The graph of the knowledge structure of the learning community $G_c = (V_c, E_c)$ has node set V_c and edge set E_c where: $V_c = \{v_1, v_2, \dots, v_n\}$ is (corresponding to tags t_1, t_2, \dots, t_n) and $E_c = \{e_1, e_2, \dots, e_n\}$. Where a set of keyword search

is $K = \{k_1, k_2, \dots, k_m\}$, and k_i is an element of K , $k_i \in V_c$, if there is $e_{ij} \in E_c$, e_{ij} is the edges corresponding to a tag $t_i (= k)$ and t_j , and the weight represented as w_{cij} . This time, let a set of t_i and t_j with Top- k (w_{cij}) be V_{cTop} . On the other hand, let the graph of the learner's knowledge structure be $G = (V, E)$. Where $V_{cTop} = \{v_1, v_2, \dots, v_n\}$, an element of V_{cTop} is $v_i \in V$, if there is $e \in E$, the weight of the edge e represented as w_{ij} .

Thus, MemberRank is calculated as follow:

$$\text{MemberRank} = \sum w_{ij} \tag{8}$$

V. THE PRELIMINARY EXPERIMENT

As shown in Figure 8, we have developed the knowledge-building support system that provides supporting information search on Web as a learning activity, and mutual support for building knowledge in the learning community. In a) of the figure, learners search information and bookmark as learning activities in the learning community. Our system represents high ranked pages from the top of search results. When learners bookmark, they register tags and semantic information in b). As shown in c), learners are able to see the knowledge structure of the learning community. As shown in d), our system recommends members, and it is possible to see the bookmarks and the knowledge structure of members. If necessary, they are able to invite members to their community.

sbm_knowledge	c_member_id	from_tag	to_tag	weight
107	34	72	67	0.99
117	35	3	76	0.98093601
114	35	17	74	1.95059601
115	35	17	75	0.950990499
123	35	24	80	0.9801
113	35	49	73	1.9212890499
126	35	74	75	0.99
128	35	75	81	0.99
119	35	78	24	0.9801
118	35	78	79	0.9801
120	35	78	80	0.9801
121	35	79	24	0.9801
122	35	79	80	0.9801
129	35	82	81	1
133	36	24	3	0.904382075009
132	36	49	3	2.845489338885
131	36	49	24	0.904382075009
136	36	49	68	0.99
130	36	49	83	0.895338254259
134	36	49	84	5.821794
135	36	49	85	0.9801
200	37	3	101	0.99
197	37	49	66	0.9801
196	37	49	85	0.970299
198	37	49	100	0.9801
201	37	49	102	1
199	37	66	100	0.9801

Figure 6. The data used to create the knowledge model of Learners

c_commu_id	from_tag	to_tag	weight
1	42	43	0.904382075009
1	42	25	0.904382075009
1	42	24	0.904382075009
1	42	42	0.895338254259
1	42	25	0.895338254259
1	44	46	0.913517247404
1	44	45	0.913517247404
1	45	46	0.913517247404
1	47	48	0.922746894428
1	49	172	0.970299
1	49	110	0.96059601
1	49	172	0.96059601
1	49	82	0.932065347907
1	49	51	0.932065347907
1	49	50	0.932065347907
1	50	49	0.99
1	50	57	0.941480149401
1	50	82	0.932065347907
1	50	51	0.932065347907
1	51	52	0.932065347907
1	56	57	1
1	56	60	0.950990499
1	56	58	0.950990499
1	56	57	0.941480149401
1	56	50	0.941480149401

c_commu_id	from_tag	to_tag	weight
4	47	48	0.922746894428
4	49	73	5.90099601
4	49	84	5.821794
4	49	3	2.845489338885
4	49	85	1.9801
4	49	105	1.940598
4	49	73	1.9212890499
4	49	169	1
4	48	24	1
4	49	102	1
4	49	145	1
4	49	65	1
4	49	146	1
4	48	148	1
4	48	144	0.99
4	48	144	0.99
4	49	65	0.99
4	49	68	0.99
4	49	147	0.99
4	49	148	0.99
4	49	138	0.99
4	49	65	0.9801
4	49	106	0.9801
4	49	100	0.9801
4	49	85	0.9801

Figure 7. The data used to create the knowledge model of the learning community

(tag_id, tag_name)=(3, php), (17, Web), (49, MySQL), (73, database), (74, html), (75, css), (84, primer), (85, Reference), (110, command), (172, dump) , (173, dumpdata), ...

In July 2011, we conducted the preliminary experiment intended for students of the information system course. As a result, as shown in Figure 6, we obtained the data used to create the learner's knowledge model. If we focus on the learner (c_member_id: 35), information about MySQL (tag_id: 49) has not hardly been collected. On the other hand, as shown in Figure 7, we obtained the data used to create the knowledge model of the learning community model. The community (c_commu_id: 1) shown on the left, has been collected information about the dump of MySQL. The community (c_commu_id: 4) shown on the right, has been collected a lot of information about entry-level MySQL. If the learner (c_member_id: 35) joins the community of right, and search "MySQL", the entry-level information about the MySQL will be recommended using the knowledge structure of the community. In addition, the community of right will be recommended to the learner as highly CommunityRank.

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed the learning environment to support information search on the Web as a learning activity, and to promote of mutually support for building knowledge in the learning community. As the technique to achieve knowledge-building support, we have developed the system to take advantage of social bookmark in the process of information search on the Web. The results of preliminary experiments, we confirmed that it is possible to extract the respective interests and objective by using the knowledge model of learners and learning community.

In the future, we continue to inquiry learning including information search process on the Web, we will evaluate the effectiveness of knowledge-building support system that focuses on the dynamic knowledge structure of the learning community.

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Figure 8. A Running Example of our System

- a) Our system presents high ranked pages from the top of search results.
- b) Learner registers tags and semantic information.
- c) Our system presents the knowledge structure of the learning community.
- d) Our system recommends members, and presents bookmarks and the knowledge structure of members.